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|  | QMRF identifier (JRC Inventory): To be entered by JRC |
| | QMRF Title: AOH: The atmospheric hydroxylation rate (LogOH) constant for the atmospheric, gas-phase reaction between photochemically produced hydroxyl radicals and organic chemicals, from the NCCT_Models Suite. |
| | Printing Date: May 4, 2016 |

1. QSAR identifier

1.1. QSAR identifier (title):

AOH: The atmospheric hydroxylation rate (LogOH) constant for the atmospheric, gas-phase reaction between photochemically produced hydroxyl radicals and organic chemicals, from the NCCT_Models Suite.

1.2. Other related models:

No related models

1.3. Software coding the model:

NCCT_models V1.02

Suite of QSAR models to predict physicochemical properties and environmental fate of organic chemicals

Kamel Mansouri (mansouri.kamel@epa.gov; mansourikamel@gmail.com);

<https://comptox.epa.gov/dashboard/>

PaDEL descriptors V2.21

Open source software to calculate molecular descriptors and fingerprints.

Chun Wei Yap (phayapc@nus.edu.sg)

<http://padel.nus.edu.sg/software/padeldescriptor>

MATLAB

MATrix LABoratory is a multi-paradigm numerical computing environment and fourth-generation programming language

http://www.mathworks.com/company/aboutus/contact_us/?s_tid=gn_cntus

<http://www.mathworks.com/products/matlab/>

2. General information

2.1. Date of QMRF:

18 April 2016

2.2. QMRF author(s) and contact details:

[1]Kamel Mansouri, ORISE research fellow at National Center for Computational Toxicology (NCCT), U.S. Environmental Protection Agency, mansouri.kamel@epa.gov; mansourikamel@gmail.com

[2]Antony Williams, National Center for Computational Toxicology (NCCT), U.S. Environmental Protection Agency, Williams.Antony@epa.gov

2.3. Date of QMRF update(s):

2.4. QMRF update(s):

2.5. Model developer(s) and contact details:

Kamel Mansouri, ORISE research fellow at National Center for Computational Toxicology (NCCT),
U.S. Environmental Protection Agency, mansouri.kamel@epa.gov; mansourikamel@gmail.com

2.6. Date of model development and/or publication:

2016

2.7. Reference(s) to main scientific papers and/or software package:

- [1] An Investigation of the Impact of Quality versus Quantity of data on the development of physicochemical parameter QSAR models. Antony Williams, Kamel Mansouri, Chris Grulke and Ann Richard
- [2] Modeling physicochemical properties and environmental fate of organic chemicals. Kamel Mansouri, Antony Williams, Chris Grulke, Ann Richard, Richard Judson
- [3] PaDEL-descriptor: an open source software to calculate molecular descriptors and fingerprints. Chun Wei Yap. (2011). J. Comput. Chem., 32: 1466–1474. doi:10.1002/jcc.21707
<http://onlinelibrary.wiley.com/doi/10.1002/jcc.21707/abstract>
- [4] A KNIME workflow for chemical structures curation and standardization in QSAR modeling. Kamel Mansouri, Sherif Farag, Jayaram Kancherla, Regina Politi, Eugene Muratov, Denis Fourches, Ann Richard, Richard Judson, Alexander Tropsha.
- [5] Williams, A., K. Mansouri, A. Richard, AND C. Grulke. The influence of data curation on QSAR Modeling – examining issues of quality versus quantity of data (SOT). Presented at Society of Toxicology, New Orleans, LA, March 13 - 17, 2016.
https://cfpub.epa.gov/si/si_public_record_report.cfm?dirEntryId=311418
- [6] Richard, A., C. Grulke, K. Mansouri, R. Judson, AND A. Williams. An Online Prediction Platform to Support the Environmental Sciences (American Chemical Society). Presented at ACS Spring Meeting, San Diego, CA, March 13 - 17, 2016.
https://cfpub.epa.gov/si/si_public_record_Report.cfm?dirEntryId=311655

2.8. Availability of information about the model:

Non-proprietary suite of QSAR models freely available on the NCCT chemistry dashboard (<https://comptox.epa.gov/dashboard>) and as a standalone application. Training and validation sets are available for visualization on the dashboard and as SDF files provided in supporting information [Section 9.3](#) and from the paper [\[ref 2, Section 2.7\]](#).

2.9. Availability of another QMRF for exactly the same model:

Not to date

3. Defining the endpoint - OECD Principle 1**3.1. Species:**

Not applicable

3.2. Endpoint:

QMRF 2. Environmental fate parameters QMRF 2. 2.b. Persistence: Abiotic degradation in air (Phototransformation), AOH

3.3. Comment on endpoint:

The atmospheric hydroxylation rate is the OH rate constant for the atmospheric, gas-phase reaction between photochemically produced hydroxyl radicals and organic chemicals expressed in logarithm values.

3.4.Endpoint units:

cm³/molecule-sec

3.5.Dependent variable:

LogOH

3.6.Experimental protocol:

The experimental data is downloaded from the EPI Suite data webpage (<http://esc.syrres.com/interkow/EpiSuiteData.htm>).

This data comes from PhysProp (The Physical Properties Database) which is a collection of a wide variety of sources built by Syracuse Research Corporation (SRC).

3.7.Endpoint data quality and variability:

The original data collected from the PhysProp database (**818**

chemicals) has undergone a series of processes to curate the chemical structures and remove duplicates, obvious outliers and erroneous entries. This procedure also included a consistency check to ensure only good quality data is used for the development of the QSAR model(**765 chemicals**).

Then, QSAR-ready structures were generated by standardizing all chemical structures and removing duplicates, inorganic and metallo-organic chemicals(**745 chemicals**). The descriptions of KNIME workflows that were developed for the purpose of the cleaning and standardization of the data are available in the papers[[ref 1](#) and [ref 4 Section 2.7](#)].

The curated outlier-free experimental data(**692 chemicals**) was divided into training and validation sets before the machine learning and modeling steps.

4.Defining the algorithm - OECD Principle 2

4.1.Type of model:

QSAR model using PaDEL descriptors[[ref2 Sect 1.3](#)].

4.2.Explicit algorithm:

Distance weighted k-nearest neighbors (kNN)

This is a refinement of the classical k-NN classification algorithm where the contribution of each of the k neighbors is weighted according to their distance to the query point, giving greater weight to closer neighbors. The used distance is the Euclidean distance. kNN is an unambiguous algorithm that fulfills the transparency requirements of OECD principle 2 with an optimal compromise between model complexity and performance.

4.3.Descriptors in the model:

[1]nBondsD2, Unitless, Bond count: Total number of double bonds (excluding bonds to aromatic bonds).

[2]C1SP2, Unitless, Carbon types: Doubly bound carbon bound to one other carbon

[3]GATS1e, Unitless, Geary autocorrelation - lag 1 / weighted by Sanderson electronegativities.

Todeschini, R. and Consonni, V. (2009). Molecular descriptors for chemoinformatics, (Weinheim: Wiley VCH) pg 27-37

[4]minwHBa, Unitless, Atom type electrotopological state: Minimum E-States for weak Hydrogen Bond acceptors. Hall, L. H., and Kier, L. B. (1995). Electrotopological state indices for atom types: A

novel combination of electronic, topological, and valence state information. *J Chem Inf Comput Sci* 35, 1039-1045; Liu, R., Sun, H., and So, S. S. (2001). Development of quantitative structure-property relationship models for early ADME evaluation in drug discovery. 2. Blood-brain barrier penetration. *J Chem Inf Comput Sci* 41, 1623-1632.; Gramatica, P., Corradi, M., and Consonni, V. (2000). Modelling and prediction of soil sorption coefficients of non-ionic organic pesticides by molecular descriptors. *Chemosphere* 41, 763-777.

[5]AATS0e, Unitless, Average Broto-Moreau autocorrelation - lag 0 / weighted by Sanderson electronegativities. Todeschini, R. and Consonni, V. (2009). *Molecular descriptors for chemoinformatics*, (Weinheim: Wiley VCH) pg 27-37

[6]maxWHBa, Unitless, Atom type electrotopological state: Maximum E-States for weak Hydrogen Bond acceptors. Hall, L. H., and Kier, L. B. (1995). Electrotopological state indices for atom types: A novel combination of electronic, topological, and valence state information. *J Chem Inf Comput Sci* 35, 1039-1045; Liu, R., Sun, H., and So, S. S. (2001). Development of quantitative structure-property relationship models for early ADME evaluation in drug discovery. 2. Blood-brain barrier penetration. *J Chem Inf Comput Sci* 41, 1623-1632.; Gramatica, P., Corradi, M., and Consonni, V. (2000). Modelling and prediction of soil sorption coefficients of non-ionic organic pesticides by molecular descriptors. *Chemosphere* 41, 763-777.

[7]maxdCH2, Unitless, Atom type electrotopological state: Maximum atom-type E-State: =CH2. Hall, L. H., and Kier, L. B. (1995). Electrotopological state indices for atom types: A novel combination of electronic, topological, and valence state information. *J Chem Inf Comput Sci* 35, 1039-1045; Liu, R., Sun, H., and So, S. S. (2001). Development of quantitative structure-property relationship models for early ADME evaluation in drug discovery. 2. Blood-brain barrier penetration. *J Chem Inf Comput Sci* 41, 1623-1632.; Gramatica, P., Corradi, M., and Consonni, V. (2000). Modelling and prediction of soil sorption coefficients of non-ionic organic pesticides by molecular descriptors. *Chemosphere* 41, 763-777.

[8]TIC1, Unitless, Total information content index (neighborhood symmetry of 1-order). Todeschini, R. and Consonni, V. (2009). *Molecular descriptors for chemoinformatics*, (Weinheim: Wiley VCH) pg 408-411.

[9]AATS1e, Unitless, Average Broto-Moreau autocorrelation - lag 1 / weighted by Sanderson electronegativities. Todeschini, R. and Consonni, V. (2009). *Molecular descriptors for chemoinformatics*, (Weinheim: Wiley VCH) pg 27-37

[10]AATS3i, Unitless, Average Broto-Moreau autocorrelation - lag 3 / weighted by first ionization potential. Todeschini, R. and Consonni, V. (2009). *Molecular descriptors for chemoinformatics*, (Weinheim: Wiley VCH) pg 27-37

[11]AATS3e, Unitless, Average Broto-Moreau autocorrelation - lag 3 / weighted by Sanderson electronegativities. Todeschini, R. and Consonni, V. (2009). *Molecular descriptors for chemoinformatics*, (Weinheim: Wiley VCH) pg 27-37

[12]nHCsat, Unitless, Atom type electrotopological state; Count of atom-type H E-State: H on C sp³ bonded to unsaturated C. Hall, L. H., and Kier, L. B. (1995). Electrotopological state indices for atom types: A novel combination of electronic, topological, and valence state information. *J Chem Inf Comput Sci* 35, 1039-1045; Liu, R., Sun, H., and So, S. S. (2001). Development of quantitative structure-property relationship models for early ADME evaluation in drug discovery. 2. Blood-brain barrier penetration. *J Chem Inf Comput Sci* 41, 1623-1632.; Gramatica, P., Corradi, M., and Consonni, V. (2000). Modelling and prediction of soil sorption coefficients of non-ionic organic pesticides by molecular descriptors. *Chemosphere* 41, 763-777.

[13]SHdsCH, Unitless, Atom type electrotopological state: Sum of atom-type H E-State: =CH-. Hall,

L. H., and Kier, L. B. (1995). Electrotopological state indices for atom types: A novel combination of electronic, topological, and valence state information. J Chem Inf Comput Sci 35, 1039-1045; Liu, R., Sun, H., and So, S. S. (2001). Development of quantitative structure-property relationship models for early ADME evaluation in drug discovery. 2. Blood-brain barrier penetration. J Chem Inf Comput Sci 41, 1623-1632.; Gramatica, P., Corradi, M., and Consonni, V. (2000). Modelling and prediction of soil sorption coefficients of non-ionic organic pesticides by molecular descriptors. Chemosphere 41, 763-777.

4.4.Descriptor selection:

PaDEL software was used to calculate **1440 molecular descriptors**.

A first filter was applied in order to remove descriptors with missing values, constant and near constant (standard deviation of **0.25 as a threshold**) and highly correlated descriptors (**96% as a threshold**).

The remaining **749 descriptors** were used in a feature selection procedure to select a minimum number of variables encoding the most relevant structural information to the modeled endpoint. This step consisted of coupling Genetic Algorithms (GA) with the weighted kNN algorithm and was applied in 5-fold cross-validation on the training set (**516 chemicals**). This procedure was run for 200 consecutive independent runs maximizing Q^2 in cross-validation and minimizing the number of descriptors. The number of k neighbors is optimized within the range of 3 to 7. The descriptors were then ranked based on their frequency of selection during the GA runs. The best model showed an optimal compromise between the simplicity (minimum number of descriptors) and performance (Q^2 in cross-validation) to ensure transparency and facilitate the mechanistic interpretation as required by OECD principles 2 and 5. More details in paper [\[ref2 Section 2.7\]](#).

4.5.Algorithm and descriptor generation:

PaDEL descriptors were calculated based on two-dimensional (2D) chemical structures generated by the Indigo cheminformatics suite of tools implemented in KNIME. 2D descriptors were selected over 3D to avoid complicated and usually irreproducible geometrical optimizations. The calculated descriptors fall into different groups such as constitutional indices, ring descriptors, topological indices, 2D matrix based descriptors, functional group counts and atom counts. Details and references provided in [Section 4.3](#).

4.6.Software name and version for descriptor generation:

PaDEL-Descriptors V2.21

An open source software to calculate molecular descriptors and fingerprints.

Chun Wei Yap (phayapc@nus.edu.sg)

<http://padel.nus.edu.sg/software/padeldescriptor>

4.7.Chemicals/Descriptors ratio:

516 chemicals (trainingset)/13 descriptors=39.69

5.Defining the applicability domain - OECD Principle 3

5.1. Description of the applicability domain of the model:

The model is applicable to heterogeneous organic chemicals. In the implementation of the model several pieces of information are given to help the user in evaluating the reliability of a prediction. The chemical structure is first assessed to see if it is falling within the Applicability Domain of the model or not. Then the accuracy of the predicted value is reported based on the similarity of the query chemical to its neighboring chemicals in the training set of the model. This fulfills the requirements of the 3rd OECD principle by defining the limitations in terms of the types of chemical structures, physicochemical properties and mechanisms of action for which the model can generate reliable predictions.

5.2. Method used to assess the applicability domain:

The applicability domain of the model is assessed in two independent levels using two different distance-based methods. First, a global applicability domain is determined by means of the leverage approach that checks whether the query structure falls within the multidimensional chemical space of the whole training set. The leverage of a query chemical is proportional to its Mahalanobis distance measure from the centroid of the training set. The leverages of a given dataset are obtained from the diagonal values of the hat matrix. This approach is associated with a threshold leverage that corresponds to $3 \cdot p/n$ where p is the number of model variables while n is the number of training compounds. A query chemical with leverage higher than the threshold is considered outside the AD and can be associated with unreliable prediction. The leverage approach has its limitations, especially when it comes to gaps within the descriptor space of the model or at the edges of the training set. That's why we added a second layer of applicability domain assessment with a local approach investigating only the vicinity of the query chemical. Contrary to the first approach that provides only Boolean answers (yes/no), this local approach provides a continuous index ranging from 0 to 1. This local AD-index is relative to the similarity of the query chemical to its 5 nearest neighbors in the p dimensional space of the model. The higher this index, the more the prediction is likely to be reliable.

5.3. Software name and version for applicability domain assessment:

Implemented in NCCT_Models Suite V1.02

An implementation of a local similarity index and the leverage approach based on the work of Sahigara, F.; Mansouri, K.; Ballabio, D.; Mauri, A.; Consonni, V.; Todeschini, R. Comparison of Different Approaches to Define the Applicability Domain of QSAR Models. *Molecules* 2012, 17, 4791-4810.

Kamel Mansouri (mansouri.kamel@epa.gov; mansourikamel@gmail.com);
<https://comptox.epa.gov/dashboard/>

5.4. Limits of applicability:

These two AD methods described in [Section 5.2](#) are complementary and can be interpreted in the following way:

- If a chemical is considered outside the global AD with a low local AD-index, the prediction is more likely to be unreliable
- If a chemical is considered outside the global AD but the local AD-index is average or relatively high, this means the query chemical is on the edge of the training set but has quite similar neighbors. The prediction can be considered with caution.
- If a chemical is considered inside the global AD but the local AD-index is average or relatively low, this means the query chemical fell in a "gap" of the chemical space of the model but still within the boundaries of the training set and surrounded with training chemicals. The prediction should be considered with caution.
- If a chemical is considered inside the global AD with a high local AD-index, the prediction can be trusted.

Even though the applicability domain is necessary to set the limits of the interpolation space of the model, it doesn't necessarily inform about the quality of the prediction especially in the empty spaces and around the edges of the descriptor space. In order to overcome this limitation and help the user decide about the reliability of a prediction, we added a confidence level index ranging from 0 to 1 relative to the accuracy of prediction of the 5 nearest neighbors to the query chemical. The higher this index, the more the prediction is likely to be reliable.

6. Internal validation - OECD Principle 4

6.1. Availability of the training set:

Yes

6.2. Available information for the training set:

Internal ID; CAS checksum; name validity; preferred name; IUPAC name; Original SMILES; QSAR-ready canonical smiles; InChI; Salt information; DSSTox GSID; Experimental reference; Consistency flag

CAS RN: Yes

Chemical Name: Yes

Smiles: Yes

Formula: No

INChI: Yes

MOL file: Yes

6.3. Data for each descriptor variable for the training set:

All

6.4. Data for the dependent variable for the training set:

All

6.5. Other information about the training set:

The training set consists of **516 chemicals**. The structures are randomly selected to represent 75% of the available data keeping a similar normal distribution of LogOH values in both training and test

sets using the Venetian blinds method. The values are ranging from --16 to --9. A plot of the distribution of LogOH values is provided in the supporting information [Section 9.3](#).

6.6.Pre-processing of data before modelling:

No preprocessing of the values.

6.7.Statistics for goodness-of-fit:

Performance in training:

$$R^2=0.85$$

$$RMSE=1.12$$

6.8.Robustness - Statistics obtained by leave-one-out cross-validation:

6.9.Robustness - Statistics obtained by leave-many-out cross-validation:

Performance in 5-fold cross-validation:

$$Q^2=0.85$$

$$RMSE=1.14$$

A plot of the experimental versus predicted values for the training set is provided in supporting information [Section 9.3](#).

6.10.Robustness - Statistics obtained by Y-scrambling:

6.11.Robustness - Statistics obtained by bootstrap:

6.12.Robustness - Statistics obtained by other methods:

7.External validation - OECD Principle 4

7.1.Availability of the external validation set:

Yes

7.2.Available information for the external validation set:

Internal ID; CAS checksum; name validity; preferred name; IUPAC name; Original SMILES; QSAR-ready canonical smiles; InChI; Salt information; DSSTox GSID; Experimental reference; Consistency flag

CAS RN: Yes

Chemical Name: Yes

Smiles: Yes

Formula: No

INChI: Yes

MOL file: Yes

7.3.Data for each descriptor variable for the external validation set:

All

7.4.Data for the dependent variable for the external validation set:

All

7.5.Other information about the external validation set:

The validation set consists of **176 chemicals**.

The values are ranging from --16 to --9.

7.6.Experimental design of test set:

The structures are randomly selected to represent 25% of the available data keeping a similar normal distribution of LogOH values in both training and test sets using the Venetian blinds method. A plot of the distribution of LogOH values is provided in the supporting information [Section 9.3](#).

7.7. Predictivity - Statistics obtained by external validation:

Performance in test:

$$R^2=0.83$$

$$RMSE=1.23$$

7.8. Predictivity - Assessment of the external validation set:

The validation set consisting of **176 chemicals** which is equivalent to a third (1/3) of the training set is sufficient for the evaluation of the predictivity of the model and a good representation of the chemical space as shown in the multi-dimensional scaling plot provided in supporting information [Section 9.3](#).

A plot of the experimental versus predicted values for the validation set is provided in supporting information [Section](#)

[9.3](#).

7.9. Comments on the external validation of the model:

The choice of proportions between the training set and the validation set as well as the splitting method helped in accurately evaluating the model and covering most of the training set chemical space. This goal was accomplished without the need to do a structural sampling that usually shows over-optimistic evaluation of the predictivity or a complete random selection that risks to bias the evaluation towards a certain region of the chemical space.

8. Providing a mechanistic interpretation - OECD Principle 5

8.1. Mechanistic basis of the model:

The model descriptors were selected statistically but they can also be mechanistically interpreted.

nBondsD2: Bond count: Total number of double bonds (excluding bonds to aromatic bonds).

C1SP2: Carbon types: Doubly bound carbon bound to one other carbon.

GATS1e: Geary autocorrelation - lag 1 / weighted by Sanderson electronegativities.

minwHBa: Atom type electrotopological state: Minimum E-States for weak Hydrogen Bond acceptors.

AATS0e: Average Broto-Moreau autocorrelation - lag 0 / weighted by Sanderson electronegativities.

maxwHBa: Atom type electrotopological state: Maximum E-States for weak Hydrogen Bond acceptors..

maxdCH2: Atom type electrotopological state: Maximum atom-type E-State: =CH2.

TIC1: Total information content index (neighborhood symmetry of 1-order).

AATS1e: Average Broto-Moreau autocorrelation - lag 1 / weighted by Sanderson electronegativities

AATS3i: Average Broto-Moreau autocorrelation - lag 3 / weighted by first ionization potential.

AATS3e: Average Broto-Moreau autocorrelation - lag 3 / weighted by Sanderson electronegativities.

nHCsatu: Atom type electrotopological state; Count of atom-type H
E-State: H on C sp³ bonded to unsaturated C.
SHdsCH: Atom type electrotopological state: Sum of atom-type H E-State:
=CH-

8.2.A priori or a posteriori mechanistic interpretation:

A posteriori mechanistic interpretation.

8.3.Other information about the mechanistic interpretation:

For more details and full reference, see references in [Section 4.3](#) and [Section 9.2](#).

9.Miscellaneous information

9.1.Comments:

This QSAR model for **LogOH** prediction is part of the NCCT_Models Suite that is a free and open-source standalone application for the prediction of physicochemical properties and environmental fate of chemicals. This application is available in the Supporting information [Section 9.3](#) of this report and in the paper [ref 2](#)

[Section 2.7](#). The detailed results of this suite of models applied on more than 700k DSSTox chemicals are available on the iCSS chemistry dashboard (<https://comptox.epa.gov/dashboard>).

This current version of the model is mainly based on curated and standardized data collected from the Physprop database. All NCCT_Models are designed to fulfil the requirement of the 5 OECD principles to ensure transparency and reproducibility of the results. In order to predict new chemicals, the models only require 2D chemical structures that are used to calculate molecular descriptors by PaDEL 2.21 software. Then a simple weighted kNN algorithm is used to make the prediction based on the observed values of the k closest molecules. All models showed high robustness and statistics stability between training, 5-fold cross-validation and the external validation set.

Considering the full applicability domain of the **692 chemicals** with available data and the same models parameters described earlier, the calibration statistics would be an **R² of 0.84** and an **RMSE of 1.16**.

9.2.Bibliography:

9.3.Supporting information:

Training set(s) Test set(s) Supporting information

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| LogP.tif | file:///Aa.ad.epa.gov/ord\RTP\Users\K-Q\kmansour\Net MyDocuments\work\Open_EpiSuite\new_curatio n\Modeling\figs\LogP_hist.tif |
| MDS_3D.tif | file:///Aa.ad.epa.gov/ord\RTP\Users\K-Q\kmansour\Net MyDocuments\work\Open_EpiSuite\new_curatio n\Modeling\figs\MDS_3D.tif |
| LogP_hist.tif | file:///Aa.ad.epa.gov/ord\RTP\Users\K-Q\kmansour\Net MyDocuments\work\Open_EpiSuite\new_curatio n\Modeling\figs\LogP_hist.tif |

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| 10.Summary (JRC QSAR Model Database) |
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10.1.QMRF number:

To be entered by JRC

10.2.Publication date:

To be entered by JRC

10.3.Keywords:

To be entered by JRC

10.4.Comments:

To be entered by JRC